PROCEEDINGS

55. IWK

Internationales Wissenschaftliches Kolloquium
International Scientific Colloquium

13 - 17 September 2010

Crossing Borders within the ABC

Automation,

Biomedical Engineering and

Computer Science

Faculty of
Computer Science and Automation

www.tu-ilmenau.de

TECHNISCHE UNIVERSITÄT
ILMENAU

Home / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=16739

Impressum
Published by

Publisher: Rector of the Ilmenau University of Technology
Univ.-Prof. Dr. rer. nat. habil. Dr. h. c. Prof. h. c. Peter Scharff

Editor: Marketing Department (Phone: +49 3677 69-2520)
Andrea Schneider (conferences@tu-ilmenau.de)

Faculty of Computer Science and Automation
(Phone: +49 3677 69-2860)
Univ.-Prof. Dr.-Ing. habil. Jens Haueisen

Editorial Deadline: 20. August 2010

Implementation: Ilmenau University of Technology
Felix Böckelmann
Philipp Schmidt

USB-Flash-Version.

Publishing House: Verlag ISLE, Betriebsstätte des ISLE e.V.
Werner-von-Siemens-Str. 16
98693 Ilmenau

Production: CDA Datenträger Albrechts GmbH, 98529 Suhl/Albrechts

Order trough: Marketing Department (+49 3677 69-2520)
Andrea Schneider (conferences@tu-ilmenau.de)

ISBN: 978-3-938843-53-6 (USB-Flash Version)

Online-Version:

Publisher: Universitätsbibliothek Ilmenau
ilmedia
Postfach 10 05 65
98684 Ilmenau

Home / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=16739

STOCHASTIC OPTIMIZATION OF POWER SUPPLY PROCESSES IN LIBERALIZED ENERGY MARKETS

Sabine Ritter; Peter Bretschneider

Fraunhofer Application Centre
Systems Technology. Ilmenau, Germany
sabine.ritter@iosb-ast.fraunhofer.de
peter.bretschneider@iosb-ast.fraunhofer.de

ABSTRACT

Next to increasingly complex boundary conditions the planning and optimization of power supply processes in liberalized energy markets are subject to an immense number of uncertainties. These uncertainties are caused by e.g. the increasingly share of fluctuating renewable feeding and forecasting errors. For power supply companies the forecasts of influencing factors are, however, the basis for every kind of planning. Therefore it is necessary to deal with these uncertainties. Within the scope of this paper a possible way for dealing with this problem in the form of solving stochastic optimization problems of power supply processes by state-of-the-art scenario tree construction methods is presented for a special decision support system. In conclusion this method is applied for the optimization model of a multi utility system.

Index Terms - stochastic optimization, power supply process, energy management system, scenario tree construction

1. INTRODUCTION

State-of-the-art decision support systems are indispensable for the optimization of power supply processes. Reasons for this are e.g. the essential modifications in the energy policy in recent years such as the German Renewable Energies Act (EEG) and the German Energy Management Act (EnWG). Attended by this the reasons are a significant increase in the share of fluctuating renewable feeding and a continuously raised number of determining factors as well as ever increasingly complex boundary conditions. These boundary conditions of power supply processes may be technical boundary conditions such as characteristic curves of generating units, maxima of transport capacities, minima and maxima of hours of operation or downtimes. There are also economic boundary conditions such as operational and maintenance costs, prices for CO_2 equivalents or grid fees. These conditions have to be modeled in an adequate way.

Energy utilities in the liberalized energy market take their operational and strategic decisions by means of decision support systems and especially the optimization models contained therein. At this, the influencing factors such as the feeding of fluctuating renewable energy, the energy demand of private and industrial energy consumers or the energy trading prices (prices of spot and contract markets, prices for primary energy carriers, etc.) are highly subject to uncertainties, because the underlying data process is stochastic, cf. [7].

The forecasts of these uncertain influencing factors are the basis for the planning of the energy utilities: The forecasts of energy demand are e.g. the basis for their submissions of the offers, their tariff classification of energy products and their balance group and schedule management.

However, forecasts are faulty, because they usually do not represent an exact duplication of the future. Furthermore, they often depend on exogenous influencing factors such as the outdoor temperature or the wind speed, which also have to be predicted. The forecasts of these factors are faulty as well and sometimes very difficult.

That means, the input data of the optimization models are already incorrect and the planning based of these models is subject to uncertainties respectively risks. If these uncertainties caused by the stochastic of the influencing factors as well as by the forecasting errors are taken into account in the optimization of the power supply processes, this optimization is called stochastic optimization.

During deterministic optimization these uncertainties are excluded, that means for the optimization model the predicted input data are the effective realizations of these factors in the future. That implies the result of a deterministic optimization calculation is optimal only if the predicted values arise precisely in the future. Since that normally does not happen, in case of deterministic optimization it is necessary to calculate with different versions of the input data. At this, the number of versions that have to be calculated can be immense, depending on the number of the uncertain decision variables of the optimization model and their exogenous influencing factors as well as on the extent of the expected forecasting errors. The quantification of the forecasting inaccuracy as well as the evaluation of the overall risk is very difficult in this connection.

In addition, the interpretation of the optimization results of the calculated versions and the following decision-making process are also extremely complex. These decisions are currently made by humans – based on personal experiences and expert knowledge. Because of the complexity of the models and the extent of the variation calculations to be evaluated these decision-making processes are a highly challenging and particularly not solvable task, which is associated with huge responsibility and therefore implies the wish for a computer-aided state-of-the-art decision support system considering the uncertainties.

One possibility to deal with these uncertainties is to model all uncertain input data as a stochastic process, which is described with the aid of a finite number of scenarios. In the recent years there was a lot of research in this field, cf. [5], [8], [11] and [12]. Within the scope of this paper based on this research one possible way to apply these theoretical considerations is presented in practice.

2. MODEL TYPES

For the planning of energy processes it is common to formulate these decision-making problems in the form of multi-stage optimization models. At this, multi-stage means that the optimization task allows a decision-making process over a longer period of time, cf. [7]. An overview over the current state of the research in the field of multi-stage optimization is given e.g. in [12].

Concerning the mathematical formulation different model types exist, e.g. the Mixed-Integer-Programming (MIP), which is normally applied for the processes discussed in this paper and therefore is detailed below.

The subject of MIP-models is, just as with models of Linear-Programming (LP), the minimization or the maximization of a linear objective function over a set, which includes all admissible solutions and is bounded by linear equations and linear inequations. These equations and inequations are modeled in the form of boundary conditions. For the boundaries of the variables it applies: At least one of the decision variable can only assume integer values, while all other decision variable are able to assume any real values. These integer values model the state variables, which are necessary in practice, such as the actual operating modes of individual power plant utilities, whose particular ranges of values are a subset of the integers and often only consist of the values 0 and 1. And this is the difference to LP-models, which do not call for integer constraints for any decision variable. The admissible set of MIP-models forms, geometrically regarded, a multidimensional convex polyhedron that means a polygon. The complexity of MIP-models is generally comparable with the complexity of nonlinear models, which is the reason for the special significance of an adequate modeling and suitable numerical solution algorithm. An extended description of MIP-models is contained e.g. in [4].

Other model types for the modeling of energy processes, which are applied in practice, are e.g. Nonlinear-Programming (NLP) and Mixed-Integer-Nonlinear-Programming (MINLP). Within the scope of this paper, however, these model types will not be investigated any further. Detailed information about NLP- and MINLP-models can be found e.g. in [4].

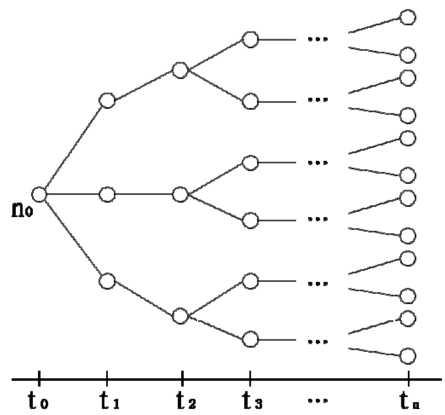

Figure 1 Example for a scenario tree with time periods $t_0, \ldots, t_n$ and the root node n_0

3. SCENARIO TREE CONSTRUCTION

One possible way to deal with uncertainties associated with energy decision problems is the usage of scenarios. Thereby, one of these scenarios corresponds to a particular outcome of a certain discrete-time multidimensional stochastic process, namely the process of the underlying input data. If the scenarios und their probabilities are suitable selected, they will form a discrete approximation of the probability distribution of the stochastic input data process. There are different methods to generate scenarios and their probabilities in such a way that they form an approximation of the random data process, cf. [6]. A survey of these methods is e.g. given in [2].

For multi-stage optimization problems besides the input data the decision stages form a discrete-time stochastic process, whereat the decisions of course depend on the input data, cf. [7].

Suitable generated sets of scenarios satisfy certain requirements: At the first time period the decision-making process is deterministic and at any other time period it depends neither on the random data process nor on the future outcomes of the data process, cf. [6]. The second feature is called nonanticipative and means that at a certain time period the decisions can only be made on the basis of the information which is currently available.

Because of these features the description of the finite set of scenarios in a tree structure, namely a *scenario tree*, is appropriated. Such a scenario tree is presented by means of example in Fig. 1.

A scenario tree consists of a finite number of *nodes*, which again consists of a bundle of scenarios sharing a common history, cf. [5]. At the first time period t_0 the scenario tree starts with the *root node* n_0, which branches into several nodes at the second time period t_1. The nodes at t_1 therefore have the root node n_0 as

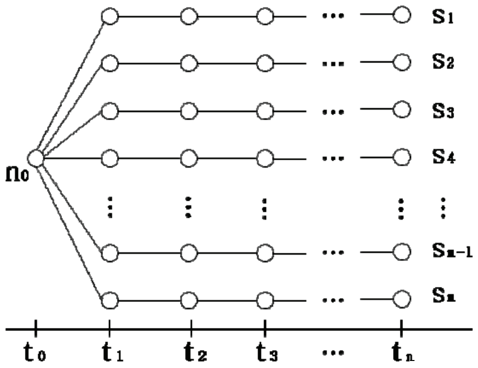

Figure 2 Example for a scenario fan with time periods $t_0, \ldots, t_n$, scenarios $s_1, \ldots, s_m$ and the root node n_0

predecessor node. All nodes also have a *transition probability* τ_n, which express with which probability the node is the *successor node* of n_0. Until the last time period t_n at every node there is the possibility of branching into a finite number of successor nodes with different transition probabilities, that means expecting the root node every node has exactly one transition probability, exactly one predecessor node but possibly several successor nodes. At this, for every node it applies: The sum of the transition probabilities of all successor nodes is 1. The *occurrence probability* of a node p_n is thereby generated recursively according to the following rule:

$$p_1 = 1, \; p_n = \tau_n * p_{n-1} \quad \text{for} \quad n \neq 1$$

Nodes, at which branching takes place, are called *branching points* and the intervals between these branching point are called *stages*, cf. [5]. The number of the *leaves* of the scenario tree, that means the nodes at the last time period t_n, is equal to the number of scenarios, because every scenario corresponds to the way from the root node to one leave, cf. [6] and [6]. The occurrence probability of a leave is therefore also the occurrence probability of the corresponding scenario.

As the probability distributions of stochastic processes can be approximated discretely by scenario trees, the question is how such scenario trees can be generated for special energy decision problems.

As also described, a sometimes very large number of different versions of the input data can normally only be taken as the basis for the decisions of the responsible persons within these power supply processes. All discrete time periods, at which decisions are made, corresponds to the stages of the scenario tree. The versions of the data can be generated e.g. by the usage of historical data or statistical models such as regressive models, cf. [6].

By these data versions a special kind of scenario tree, a so called *scenario fan*, can be created. Such a scenario fan is presented by means of example in Fig. 2.

A multi-stage decision process, however, can't be modeled adequately by such a scenario fan. This is the reason why is it necessary to generate a scenario tree out of such a scenario fan in such a way that information is revealed in every stage of the model, cf. [6]. An algorithm for such a construction of scenario trees out of scenario fans is presented in [6]. Therefore the number of nodes of the origin scenario fan is reduced by the modification of the tree structure and the bundling of similar scenarios based on a recursive reduction argument using transportation metrics, cf. [6].

In the following sections is it described how this algorithm is applied successfully in an energy management system.

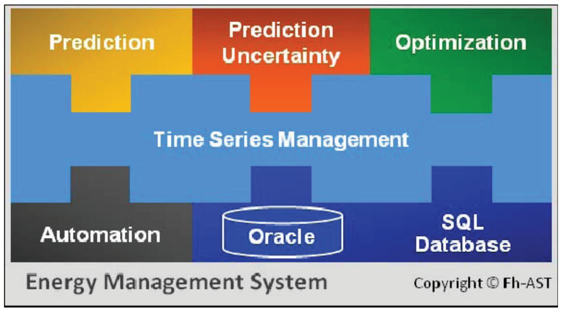

Figure 3 Concept of the energy management system

4. ENERGY MANAGEMENT SYSTEM

A software system for an adequate modeling of all relevant energy processes in line with the current energy policies and considering the uncertainties such as the non-replicable influencing factor of the fluctuating feeding of renewable energies is the energy management system (EMS) developed by the Fraunhofer Anwendungszentrum Systemtechnik Ilmenau (AST). It is a powerful and versatile IT-tool for solving problems in the fields of forecasting and optimization, with which individual workflows can be created for every project. With an automation component of the energy management system these workflows can be triggered by time or event. The basis of the overall system is a high-performance time series management. The modular structure of the EMS is presented in Fig. 3.

One main task of the EMS is the forecasting of future energy demand for the sectors electricity, gas and heating. Within the forecasting module there are different forecasting models available such as reference day search, pattern-based forecast, ARMA, ARMAX, fuzzy or Artificial Neural Networks.

The complex problems of the optimization of power supply processes are another main task of the EMS. Within the optimization module these problems can be modeled in an adequate way and be solved. The mathematical formulation of these optimization models is carried out by the General Algebraic Modeling System (GAMS). Within the optimization module there is an extensive library of model types for this formulation, inter alia LP, MIP, NLP and MINLP.

A graphic editor is use for the modeling of such a power supply process. Thereby, all relevant systems such as trading activities (on the supply as well as on the demand side), power plant utilities, storages and up- and downstream supply grids for the fields of electrici-

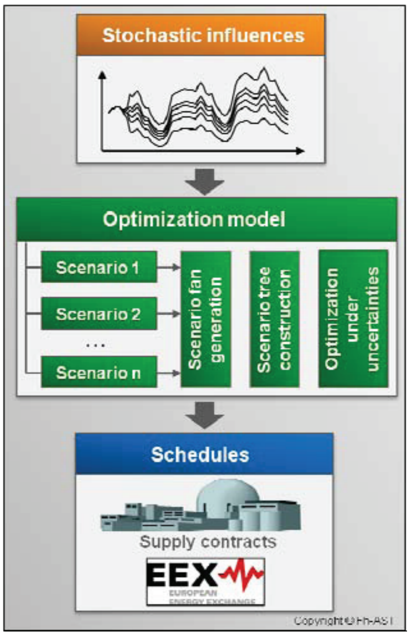

Figure 4 Workflow for the stochastic optimization

ty, gas, water, heating and cooling as well as their combination systems can be modeled and parameterized.

These models with the included components are the basis for the optimization, for which two variant exists within the EMS: The "deterministic" and the "stochastic" optimization.

4.1 Deterministic Optimization

In the deterministic variant per model exactly one version of the data of the variable influencing factors are entered for the included components. Such an optimization model with the entered version of the variable influencing factors can then be solved with every solver that is supported by GAMS and is able to use deterministic optimization methods (CPLEX, GUROBI, SBB, AlphaECP, etc.).

Schedules for every component, which is included in the optimization model, are the results of a deterministic optimization with the EMS that means these schedules satisfy a given optimization criteria for this concrete version of the influencing variables.

4.2 Stochastic Optimization

In contrast the stochastic variant of the optimization within the optimization module of the EMS offers the possibility to take the uncertainties, which are caused inter alia by non-replicable influencing factors as well as by forecasting errors, into consideration. To solve such an optimization problem numerically the stochastic of the influencing variables is modeled by a finite number of scenarios. The workflow is presented in Fig. 4.

In the stochastic variant the modeling of the power supply processes is also done by the graphic editor of the optimization module. For every optimization model there is the possibility to enter a finite number of scenarios considering their occurrence probability for the included components in the form of different outcomes of the uncertain influencing factors. These influencing

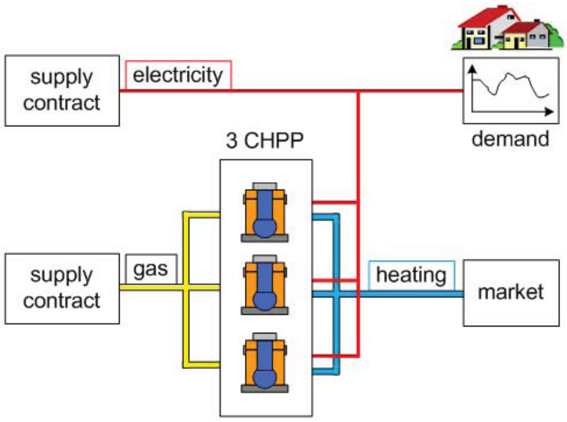

Figure 5 Structure of the optimization model

factors are called *stochastic variables* and can only be entered as time series.

The solution of such an optimization model with the entered values of the stochastic variables for the associated components can also be solved with every "deterministic" solver that is supported by GAMS. Within the stochastic optimization additional stochastic methods are automatically used in the optimization module independent from the selected solver.

In the case of a stochastic optimization the optimization module automatically detects all stochastic variables within the model that means all variables for which different input data are entered for at least two scenarios. Depending of the number of time periods and of the number of scenarios a scenario fan is generated and the input data of all stochastic variables are entered at its nodes. Afterwards a scenario tree is constructed out of this scenario fan by the algorithm, which is presented in [6] and is described in section 3. Several parameters can be set and several methods can be selected within this procedure.

Then this scenario tree is the basis for the optimization under uncertainties and schedules for all components that are included in the model are the result of this optimization as well. But in this variant the schedules do not only fulfill a given optimization criteria, in addition they are robust against the future outcomes of the included uncertain influencing factors, because every entered versions of these factors as well as their occurrence probability are taken into consideration within the stochastic optimization.

5. EXAMPLE OF USE

In the following section an example of use for the stochastic optimization of energy supply processes within the EMS is presented. For the reason of comparability the optimization model was optimized with the stochastic variant as well as with the deterministic variant. It is formulated as a MILP model and includes a combined system. Its structure is presented in Fig. 5.

On the supply side there are two supply contracts, one for electrical power with a unit charge of 5 ct/kWh and one for gas with a unit charge of 2.5 ct/kWh and on the generation side there are 3 Combined Heat and

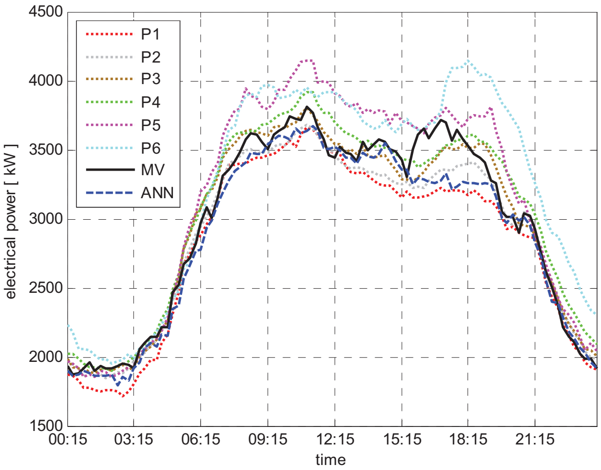

Figure 6 Measured load curve (MV), forecast (ANN) and scenarios of the electricity demand ($P_1,\ldots,P_6$)

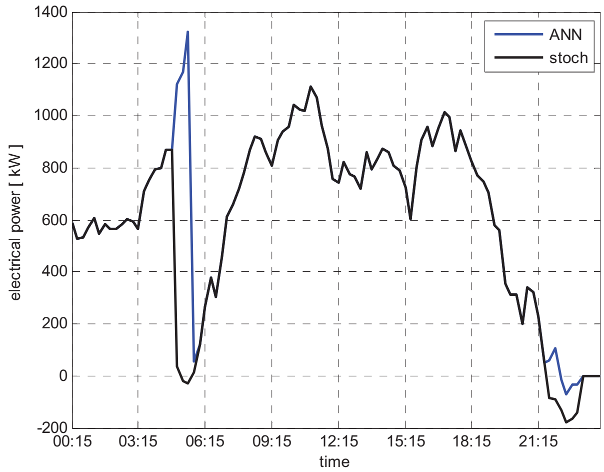

Figure 7 Electricity supply for the 2nd optimizations

Power Plants (CHPP) with temperature-dependent degrees of efficiency. On the demand side electricity demand of the end costumers as well as a market for heating with a market price of 2 ct/kWh is modeled. The influencing factor that varies within the two cases of optimization is the electricity demand. The basis for this is a real electricity load curve with measured values from the 02.01.2007 to the 31.07.2010 with a temporal resolution of 15 min. The inspection period for the optimization is the 11.05.2009 and the load curve of the measured values (MV) for this day is shown in Fig. 6.

The goal of the optimizations is the planning of cost-optimal supply and generation under the condition of satisfying the demand. Because of the Basic Model of Balancing Services and Balancing Rules in the German Gas Sector (GABI Gas) and the German Electricity Grid Access Regulation (StromNZV) within such energy supply processes the planed energy supply for the next day has to be expelled as a binding schedule and reported to the relevant market participants every day. Because the forecasts of energy demand never correspond exactly to the real demand, however, there are daily deviations between the reported schedule and the real demand. Therefore minimizing these deviations is the difficulty within these optimization problems.

In this experiment for both optimization variants the model was optimized with an assumed electricity demand. Afterwards, the calculated gas supply was fixed assuming it was reported to other market participants as a binding schedule. Then the model was optimized once again, but this time with the measured values of the electricity demand. So, supply sided only the electricity supply can be varied within these second optimizations and the deviations to the calculated electricity supply of the first optimizations can be measured.

5.3 Electricity demand for deterministic optimization

For the deterministic variant a forecast is made for the electricity demand at this day by using Artificial Neural Networks (ANN). A detailed description of ANN is given e.g. in [3]. Within the forecasting module of the EMS from the 01.01.2008 to the 31.12.2009 the ANN was trained with the measured values of the electricity load curve, a forecasted and a measured weather curve and with the aid of a calendar function provided by the forecasting module. Afterwards, the electricity demand was forecasted with this trained ANN. This variant of optimization is called ANN and the resulting forecasted load curve (ANN) can be seen in Fig. 6.

5.4 Electricity demand for stochastic optimization

For the stochastic variant 6 scenarios for the electricity demand with their occurrence probabilities were generated out of the measured load curve. This variant of optimization is called "stoch". The scenarios are called $P_1,\ldots,P_6$ and can also be seen in Fig.6. The occurrence probabilities are 0.1025641 for P_1, 0.3076923 for P_2 and P_4, 0.1538461 for P_3, 0.0512821 for P_5 and 0.0769231 for P_6.

5.5 Analysis of the results

The results of the first optimizations with the forecasted electricity demand for the deterministic variant and the 6 scenarios of electricity demand for the stochastic variant of optimization are shown in Table 1.

	Determ. Opt.	Stoch. Opt.
electr. demand [kWh]	277313.7	288077.7
electr. supply [kWh]	52926.6	58812.5
gas supply [kWh]	569477.8	581236.0
electr. generation [kWh]	216401.6	220869.7
therm. generation [kWh]	256265.0	261556.2

Table 1 Results of the first optimizations

For the second optimizations with the fixed gas supplies and the real measured values for the electricity demand the results for gas supply and therefore for electrical and thermal generation are the same as in Table 1. All other results are shown in Table 2.

	Determ. Opt.	Stoch. Opt.
electr. demand [kWh]	344177.6	344177.6
electr. supply [kWh]	61843.1	58063.1
balancing energy [kWh]	9687.6	7978.6
total costs [ct]	1299304.3	1272664.4

Table 2 Results of the second optimizations

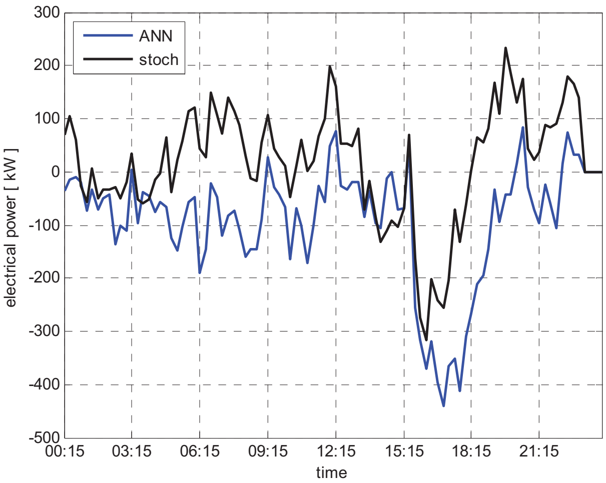

Figure 8 Required balancing energy for the 2nd optimizations

For the deterministic (ANN) and the stochastic variant (stoch) the resulting electricity supplies are shown in Fig. 7 and the required balancing energies in Fig. 8. It can be seen that the balancing energy for the stochastic variant is less than for the deterministic variant. Therefore a reduction of total costs of 266.4 € could be achieved for the inspected day, which means 2.05 % of the total costs in the deterministic case.

6. CONCLUSIONS

Within the scope of this paper a possible way to solve stochastic optimization problems by state-of-the-art methods for construction of scenario trees is presented for a specially selected decision support system. With the aid of the stochastic optimization of the energy management system presented in this paper it is possible to calculate schedules considering uncertainties for all components, which are included in the optimization model, by entering different versions of uncertain influencing factors as input parameters of the stochastic optimization model. Therefore the energy management system of the Fraunhofer AST is a suitable tool for the optimization of power supply processes, because it enables the user to take the unavoidable uncertainties respectively risks into account that are typical for these processes.

7. OUTLOOK

For the quantification of the discussed forecasting errors a method for the forecasting module of the EMS is developed at the Fraunhofer AST, which enables the user to quantify and to evaluate the risks that are caused by the forecasting uncertainties by a combination of several stochastic methods. Thus, the combination of this method with the stochastic optimization will make the EMS of the Fraunhofer AST a suitable tool for the holistic planning and optimization of power supply processes considering the unavoidable uncertainties respectively risks that are typical for these processes.

8. REFERENCES

[1] Bretschneider, P., „Systemtechnische Methoden zur optimalen Betriebsführung elektrischer Energiesysteme“, 43. Regelungstechnisches Kolloquium, Boppard, 02/2009.

[2] Dupačová, J., G. Consigli, and S.W. Wallace, “Scenarios for multistage stochastic programs”, Annals of Operations Research 100, pp. 25–53, 2000.

[3] Eisenbach, D.: Künstliche Neuronale Netze zur Prognose von Zeitreihen. Degree thesis, Westfälische Wilhelms-Universität, Münster, 2005.

[4] Floudas, Ch.A., Nonlinear and Mixed-Integer Optimization, Oxford University Press, New York, 1995.

[5] Gröwe-Kuska, N., K.C. Kiwiel, M.P. Nowak, et al., “Power management under uncertainty by Lagrangian relaxation”, Proceedings of the 6th International Conference Probabilistic Methods Applied to Power Systems PMAPS 2000, Volume 2, INESC Porto, 2000.

[6] Gröwe-Kuska, N., H. Heitsch, and W. Römisch, “Scenario Reduction and Scenario Tree Constuction for Power Management Problems”, Power Tech Conference Proceedings, Volume 3, IEEE Bologna, 2003.

[7] Heitsch, H., Stabilität und Approximation stochastischer Optimierungsprobleme, Dissertation, Humboldt-Universität zu Berlin, 2007.

[8] Nürnberg, R., and W. Römisch, “A two-stage planning model for power scheduling in a hydro-thermal system under uncertainty”, Optimization and Engineering 3, pp. 355–378, 2002.

[9] Ritter, Se., „Optimierung energiewirtschaftlicher Versorgungsprozesse“, Fraunhofer-IITB VisIT [Energie], pp. 8-9, 03/2006.

[10] Ritter, Se., and P. Bretschneider, „Optimale Planung und Betriebsführung der Energieversorgung im liberalisierten Energiemarkt“, 52. Internationales Wissenschaftliches Kolloquium, Technische Universität Ilmenau, 09/2007.

[11] Sen, S., L. Lihua Yu, and T. Genc, “A stochastic programming approach to power portfolio optimization”, Technical report, Raptor Laboratory, SIE Department, University of Arizona, Tucson, 2002 and Stochastic Programming E-Print Series 02/2003 (<www.speps.info>).

[12] Wallace, S.W., and S.-E. Fleten, “Stochastic programming models in energy”, Working paper 01-02, Dept. of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway, 2002.